Estimating DR Load Impacts: Evaluation of baseline load models for commercial buildings in California

Preliminary Results

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Overview of Talk

- **Introduction**
  - define problem and LBNL's analytical approach
  - define criteria used to characterize and evaluate model performance
- **Baseline load models**
  - define the models and discuss use of adjustment factors
  - categorize buildings based on load characteristics
  - define our statistical measures of bias and accuracy, and present results by building and by model
  - compare the current BLM used in some California programs (3 in 10 days without adjustment) to alternative models
- **Summarize what we have learned so far**

Problem statement

- On an *event day*, customers modify their building loads away from normal operation with the goal of reducing electric loads
- The customer's load that would have occurred on the event day with no DR is termed the *baseline*
- A number of *baseline models* (BLMs) exist that allow the baseline to be estimated from historic building load and weather data
- Project Goal:
  - Evaluate the performance of these baseline models for commercial and light manufacturing buildings in California, with respect to accuracy, bias and predictive ability

LBNL Analytical Approach

- **Develop a method that allows a statistical evaluation of BLM for individual customers**
- ***Compare BLM used in some CA DR programs with alternatives***
- **Sample: 32 buildings in the auto-DR pilot with 1-2 years of hourly interval data**
- **Define a set of *proxy event days***
  - ***Criteria:* similar weather to historical event days in CA**
  - **~60 proxy event days for each site from 2005-06 data, which is sufficient to assess performance of different BLM**
- **For each proxy event day, calculate the load predicted by a BLM and compare it to the actual load on that day**

Definition of proxy event days

- **We start with a set of *admissible days***
  - **defined as normal working days---weekdays excluding holidays and event days**
- **Use data for the months May through October**
- **From hourly temperature data at weather stations near the building sites, calculate a temperature time series for each CPP zone**

- **Based on the hourly temperature, for each zone:**
  - **Calculate daily cooling-degree hours (cdh)**
  - **Sort admissible days on the magnitude of cdh**
  - **Select the top 25% as proxy event days**

- **About 2/3 of actual event days would be selected for the proxy event day set by this method**

BLM Performance criteria

- **We discuss several issues related to the usefulness of a BLM:**

1) **Is the method *biased*: does it tend to predict baseline loads that are consistently above or below the actual loads?**
2) **Is the method *accurate*: how large is the difference between the predicted load and the actual load?**
3) **What is the relationship between building load characteristics and the bias/accuracy of the BLM?**

Morning Adjustment Factor in BLM

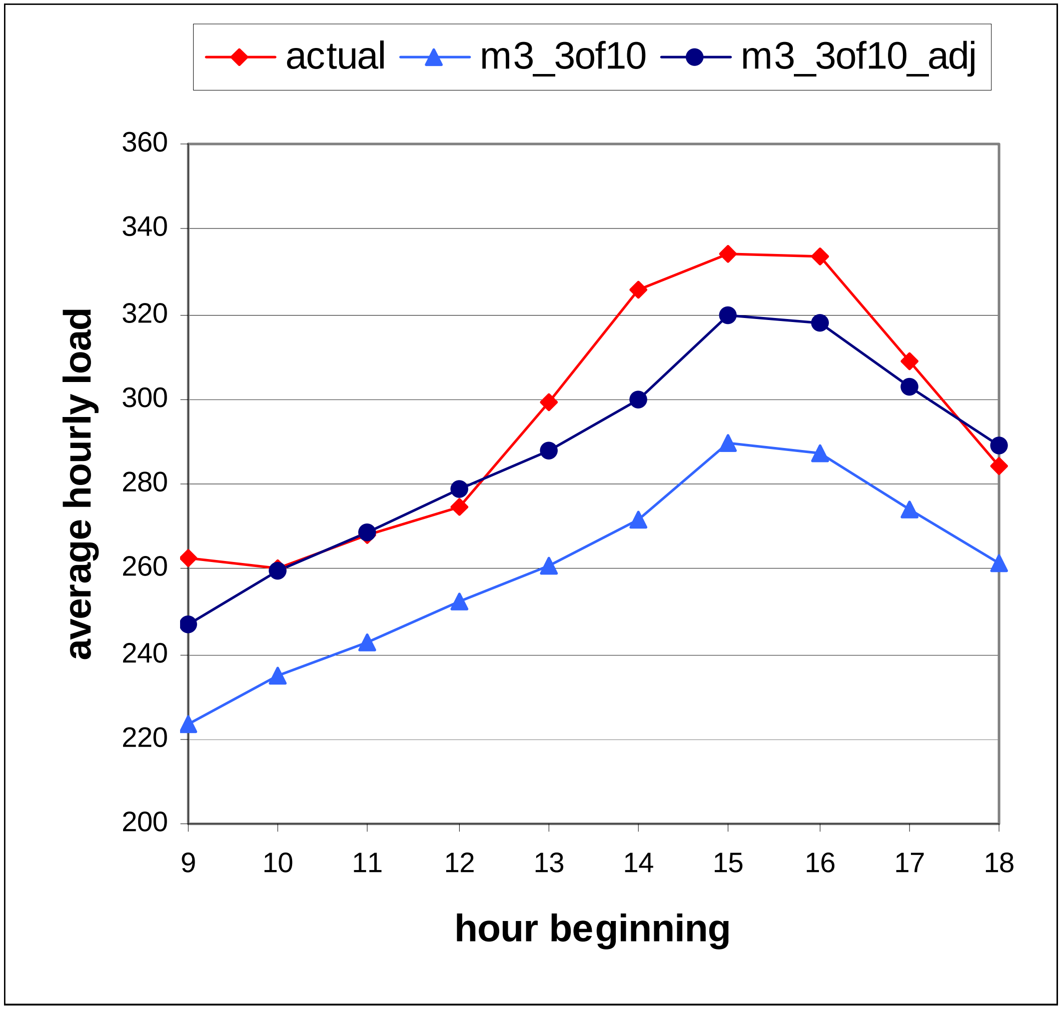
- **Morning adjustment factor may be used to calibrate the BLM to the actual load on an event day, before the event period begins**
  - **assumed to capture the effects of that day's weather, or changes to typical building operation or schedule**
- **We use a multiplicative factor**
  - **the adjusted load is $pl_{d,h} * c_d$**
  - **c_d is ratio of actual to predicted average load over the two hours immediately preceding the event period**
- **We find that using the morning adjustment reduces both the bias and the magnitude of the error for all models**

Baseline Models considered to date

Code	Model Name	Description
m1	SimpleAvg	simple average over previous 10 admissible days
m2	Enernoc	Enernoc averaging formula using previous 20 admissible days
m3	3of10	simple average over the highest 3 out of 10 previous admissible days
m4	5of10	simple average over the highest 5 out of 10 previous admissible days
m5	lt_seasonal	hourly load-temperature regression model based on one season of summer data
m6	lt_10day	hourly load-temperature regression model based on data for 10 previous admissible days
m7	lt_seasonl_tb60	hourly load-temperature regression model based on one season of data, Temp>60
m8	pjm	used by PJM: highest 5 of 10 previous admissible days with weather correction

- **Current practice in California is the 3of10 model with no same-day adjustment**
- **We present results for the 3of10 model both with the adjustment (*m3*) and without the adjustment (*m3n*)**
- **For all the other models the results are *with* the same-day morning adjustment applied**

Fremont CA Office Building: July 21st 2006



m3_3of10 load model

- Highest 3 of previous 10 admissible days

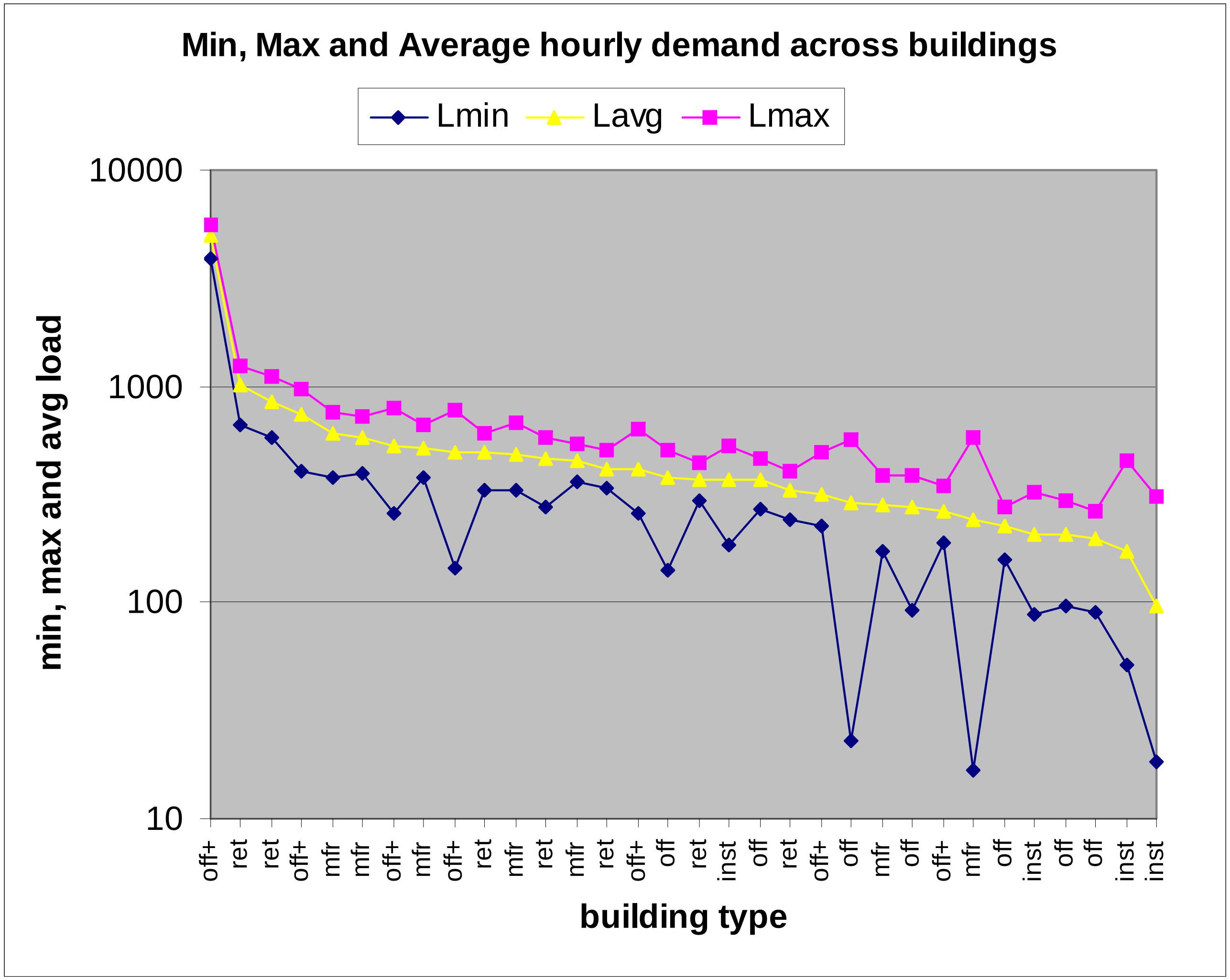
- Comparison between the actual load (red), the model with no morning adjustment (light blue) and the model with adjustment (dark blue)

- In this case the predicted load from the model is less than the actual load during the event period (12-6pm)

Building load characteristics

- **Assess weather sensitivity and load variability of each sites' loads**
  - Define high (h) and low (l) categories
- **Load variability**
  - measured by deviation from the sample average load
  - high variability is defined by deviation > 15%; a value which is comparable to the largest sheds
- **Weather sensitivity**
  - characterized using *rank-order correlation (ROC)* between hourly temperature time series and hourly loads
  - ROC is a robust indicator of the degree to which the load and temperature go up and down in the same pattern
- **We segment our sample of 32 sites using load variability and weather sensitivity (high-high, high-low etc.)**

Variability in building demand for summer days



- **Variability is defined as the variation in the load in a given daytime hour (9am-6pm), across the set of sample days**
- **It is measured by calculating the sample mean of the load in a given hour, and then calculating the average deviation from the sample mean**
- **To define a single variability measure for each building, we then average the variability over all hours**

Categorization of buildings by load variability (VAR) and weather sensitivity (ROC)

Site	Type	ROC	VAR	var	ws	Site	Type	ROC	VAR	var	ws
WalmartF	ret	0.97	0.20	h	h	SafewayS	ret	0.93	0.10	l	h
Target_Bak	ret	0.91	0.19	h	h	Solectron05	mfr	0.88	0.11	l	h
CCC_Arnold	off	0.83	0.22	h	h	Target_Ant	ret	0.83	0.13	l	h
CCC_Douglas	off	0.82	0.27	h	h	Target_Hay	ret	0.83	0.10	l	h
Solectron07	off	0.77	0.19	h	h	Echelon	off	0.82	0.14	l	h
CCC_MDF	inst	0.71	0.24	h	h	Sybase02	off	0.79	0.11	l	h
Solectron01	mfr	0.65	0.17	h	l	Gilead02	off+	0.79	0.15	l	h
Solectron04	mfr	0.63	0.15	h	l	IKEA_EPA	ret	0.77	0.10	l	h
Solectron08	off	0.60	0.32	h	l	ODC	off+	0.75	0.10	l	h
**Chabot*	*inst*	*0.49*	*0.29*	*h*	*l*	ACWD	off+	0.75	0.15	l	h
Gilead03	off+	0.49	0.18	h	l	Sybase01	off	0.74	0.14	l	h
OracleR	off	0.40	0.29	h	l	IKEA_Em	ret	0.71	0.12	l	h
Solectron09	mfr	0.36	0.63	h	l	Solectron02	mfr	0.64	0.11	l	l
Solectron06	off	0.17	0.96	h	l	Gilead01	off	0.61	0.13	l	l
**Centerville*	*inst*	*-0.05*	*0.41*	*h*	*l*	Solectron03	mfr	0.45	0.14	l	l
**Irvington*	*inst*	*-0.23*	*0.34*	*h*	*l*	Svenhards	mfr	0.01	0.11	l	l

**Three buildings have non-standard schedules: Centerville and Irvington are closed June-August, Chabot is closed Mon-Tue*

Statistical Error Measures

- **For each proxy event day (d) and event period hour (h), we calculate the predicted load** $pl_{d,h}$ **and compare to the actual load** $al_{d,h}$

- **Define the *percent hourly error* (or relative error)**

$$e_{d,h} = (pl_{d,h} - al_{d,h}) / al_{d,h}$$

- **Combining all hours and proxy event days gives a distribution of values of** $e_{d,h}$ **for each model and building**

- **Model Bias: use *median value* to quantify**
- **Model accuracy: use the average magnitude of the error to quantify**
  - **the average of the absolute value** $|e_{d,h}|$

Bias measure: median of $e_{d,h}$ by building/model

site	var	ws	m1	m2	m3	m3n	m4	m5	m6	site	var	ws	m1	m2	m3	m3n	m4	m5	m6
CCC_Arnold	h	h	0.0	0.1	-0.6	1.3	-0.5	4.4	1.6	ACWD	l	h	-2.4	-2.7	0.1	1.9	-0.5	1.1	0.1
CCC_Douglas	h	h	0.7	0.5	-0.9	1.6	-0.7	7.5	1.1	Echelon	l	h	-1.9	-2.0	-0.6	-1.5	-0.9	0.2	-0.6
CCC_MDF	h	h	-0.6	-0.8	0.4	-0.3	0.2	-0.6	0.0	Gilead02	l	h	0.7	0.6	0.6	-0.5	0.8	-0.4	0.4
Solectron07	h	h	-2.3	-2.4	0.9	1.1	0.1	-4.7	0.2	IKEA_Em	l	h	1.0	1.4	-0.1	-0.9	0.4	1.2	0.4
Target_Bak	h	h	-0.9	-0.5	-0.4	1.7	-0.5	-1.0	-0.2	IKEA_EPA	l	h	-0.7	-0.9	-0.1	2.7	-0.4	0.6	0.0
WalmartF	h	h	-0.3	-0.4	-0.5	1.7	-0.5	-1.1	-0.3	ODC	l	h	1.7	1.3	0.4	0.5	0.7	3.3	0.7
*Centerville	h	l	-7.1	-7.2	-7.9	3.5	-7.8	0.2	0.0	SafewayS	l	h	-1.6	-1.6	-0.3	1.0	-0.5	0.3	-0.3
*Chabot	h	l	1.2	3.4	1.5	3.4	1.6	4.4	1.6	Solectron05	l	h	-1.0	-1.3	0.4	0.3	0.1	0.3	0.2
*Irvington	h	l	-0.2	0.1	-3.9	4.4	-3.4	1.6	2.6	Sybase01	l	h	-4.0	-5.3	-1.6	-1.9	-2.4	-0.1	-3.2
Gilead03	h	l	-4.7	-4.9	-2.5	1.3	-3.5	-1.9	-0.7	Sybase02	l	h	-3.4	-3.9	-0.5	0.0	-2.1	-1.0	-1.1
OracleR	h	l	-1.4	-2.0	-0.1	1.9	-0.2	-2.1	0.2	Target_Ant	l	h	-0.7	-0.8	0.1	0.6	-0.2	-0.2	0.2
Solectron01	h	l	-1.4	-1.1	1.2	2.3	0.0	-0.7	-0.2	Target_Hay	l	h	-2.0	-2.2	-0.2	0.3	-0.6	0.0	0.4
Solectron04	h	l	-2.7	-2.9	-0.6	2.2	-1.4	-4.8	-1.6	Gilead01	l	l	-2.1	-1.9	1.0	-0.2	-0.7	0.7	-0.3
Solectron06	h	l	-1.0	-1.3	1.0	2.7	0.7	8.3	0.9	Solectron02	l	l	0.2	-0.5	0.9	1.0	0.5	0.9	-0.8
Solectron08	h	l	-0.4	-0.8	-0.2	0.3	-0.4	6.7	-1.2	Solectron03	l	l	-0.9	-1.1	0.4	2.5	-0.6	1.4	-0.8
Solectron09	h	l	-2.9	-3.1	-0.9	7.0	-1.6	-11.1	1.0	Svenhards	l	l	0.6	0.8	-1.0	3.3	0.0	0.2	-0.1

yellow	best performance (lowest median in absolute value)
pink	worst performance (highest median in absolute value)

m1=simple average; m2=Enernoc; m3=3of10;

m4=5of10; m5=seasonal load-temp; m6=10day load-temp

Accuracy measure: average magnitude of the percent error $e_{d,h}$ by building/model

site	var	ws	m1	m2	m3	m3n	m4	m5	m6	site	var	ws	m1	m2	m3	m3n	m4	m5	m6
CCC_Arnold	h	h	3.9	4.0	4.2	8.3	3.8	5.9	4.8	ACWD	l	h	5.3	5.2	5.3	9.0	5.3	4.2	4.9
CCC_Douglas	h	h	7.5	7.5	8.7	10.9	8.0	11.2	8.6	Echelon	l	h	4.3	4.3	4.4	8.3	4.3	3.6	4.5
CCC_MDF	h	h	7.9	7.7	10.0	9.1	8.6	7.2	8.2	Gilead02	l	h	4.4	4.1	4.6	5.2	4.2	4.8	4.9
Solectron07	h	h	5.3	5.4	5.8	11.4	5.3	6.8	5.1	IKEA_Em	l	h	2.5	2.5	2.6	5.1	2.6	2.6	2.5
Target_Bak	h	h	3.0	2.9	3.9	5.4	3.4	3.0	3.5	IKEA_EPA	l	h	4.7	4.7	4.8	5.1	4.9	4.1	5.2
WalmartF	h	h	1.9	2	2.1	4.8	2	2	2.1	ODC	l	h	2.4	2.1	1.9	3.2	2.1	4.1	2.8
*Centerville	h	l	31.0	31.6	32.8	51.6	32.3	44.5	34.6	SafewayS	l	h	2.7	2.5	2.4	3.9	2.3	2.1	2.0
*Chabot	h	l	15.0	15.8	16.2	23.8	15.4	14.9	18.2	Solectron05	l	h	2.6	2.7	2.8	5.6	2.7	1.9	2.4
*Irvington	h	l	18.9	20.7	17.9	31.4	18.1	27.5	22.7	Sybase01	l	h	5.8	6.7	5.3	7.4	5.1	4.3	5.1
Gilead03	h	l	10.6	10.6	12.5	16.4	11.1	8.1	11.4	Sybase02	l	h	5.1	5.4	4.8	7.3	4.8	3.3	3.9
OracleR	h	l	3.6	3.7	3.6	7.4	3.5	4.6	3.6	Target_Ant	l	h	2.0	2.1	2.2	3.8	2.0	2.2	2.3
Solectron01	h	l	5.8	5.7	6.3	8.2	5.8	6.1	6.0	Target_Hay	l	h	4.2	4.2	4.2	6.1	4.1	2.7	3.5
Solectron04	h	l	5.1	5.1	4.9	8.1	4.9	6.1	4.4	Gilead01	l	l	4.4	4.4	4.6	6.0	4.3	4.2	5.1
Solectron06	h	l	7.7	7.8	10.8	29.4	9.1	12.1	12.0	Solectron02	l	l	5.2	5.0	6.0	6.1	5.3	5.3	5.7
Solectron08	h	l	4.7	4.8	5.0	9.1	4.8	9.3	5.1	Solectron03	l	l	5.4	5.3	6.2	7.8	5.7	5.3	6.4
Solectron09	h	l	7.2	7.0	8.7	26.5	8.0	13.9	10.8	Svenhards	l	l	4.4	4.3	5.1	5.4	4.6	6.6	5.4

yellow	**best performance (lowest magnitude)**
pink	**worst performance (highest magnitude)**

m1=simple average; m2=Enernoc; m3=3of10;

m4=5of10; m5=seasonal load-temp; m6=10day load-temp

Sample Averages of Bias and Accuracy measures

Error Bias Measure averaged over buildings

var	ws	m1	m2	m3	m3n	m4	m5	m6
all	all	1.6	1.9	1.0	1.7	1.1	2.3	0.7
h	h	0.8	0.8	0.6	1.3	0.4	3.2	0.6
h	l	2.3	2.7	2.0	2.9	2.1	4.2	1.0
l	h	1.8	2.0	0.4	1.0	0.8	0.7	0.6
l	l	1.0	1.1	0.8	1.8	0.5	0.8	0.5

Error Magnitude Measure averaged over buildings

var	ws	m1	m2	m3	m3n	m4	m5	m6
all	all	6.4	6.5	6.9	11.2	6.5	7.6	7.1
h	h	4.9	4.9	5.8	8.3	5.2	6.0	5.4
h	l	11.0	11.3	11.9	21.2	11.3	14.7	12.9
l	h	3.8	3.9	3.8	5.8	3.7	3.3	3.7
l	l	4.9	4.8	5.5	6.3	5.0	5.4	5.7

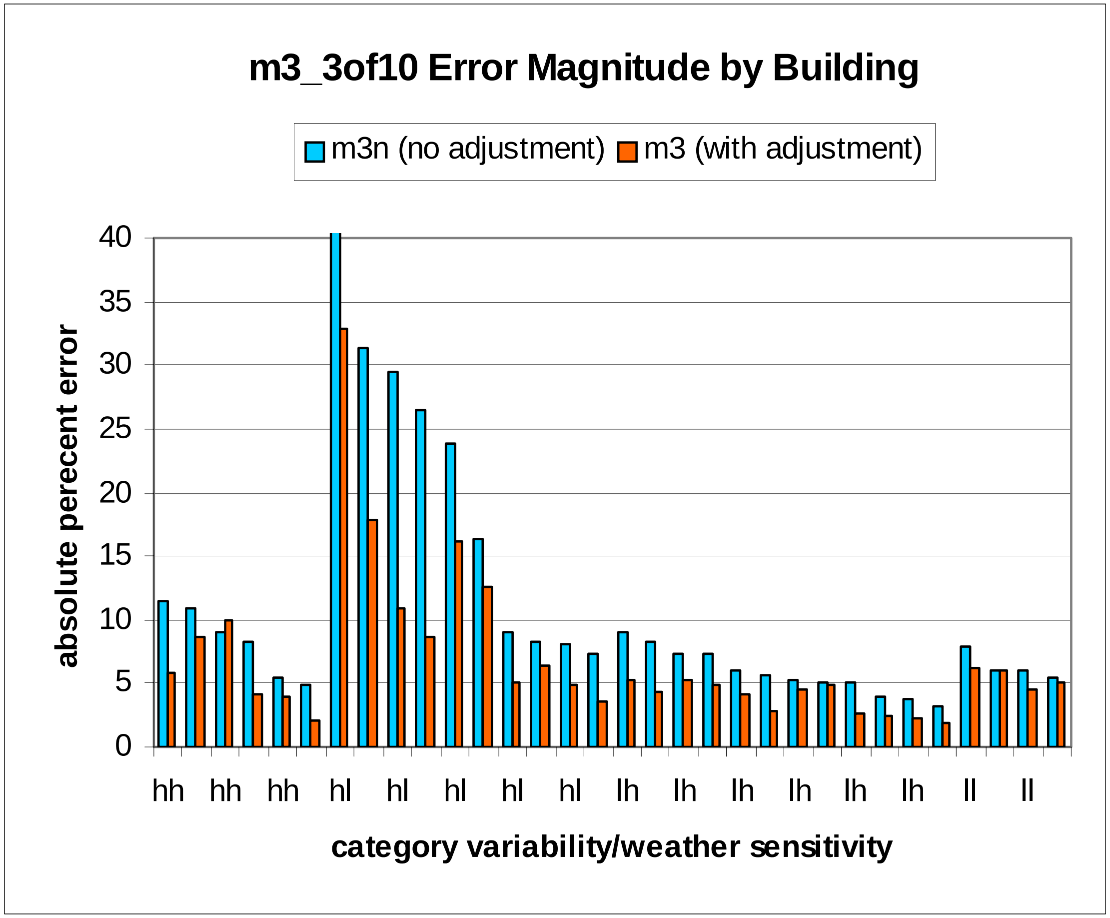
m1=simple average; m2=Enernoc; m3=3of10; m4=5of10; m5=seasonal load-temp; m6=10day load-temp

Best

Worst

- **Bias: m6 is best even for low weather sensitivity; m3 with adjustment is also good; averaging methods tend to be biased even with the same-day adjustment**
- **Magnitude: m3n model (current practice) is the worst (least accurate); otherwise there is no clearly superior model; low variablity buildings have low error magnitude for all models; weather modeling reduces the error for high variability/high weather sensitivity**

Use of morning adjustment factor for the 3of10 model



m3_3of10 load model

- highest 3 of previous 10 admissible days
- for each building the error magnitude is shown for model predictions both with and without the morning adjustment factor
- buildings are ordered by category
- adjustment reduces the error magnitude most for high var-high ws and low var-high ws

Summary of findings on Baseline Load Models for estimating DR Load Impacts

1) The existing Baseline Model (3 in 10 with no adjustment) used in CA DR bidding, capacity and CPP tariffs could be significantly improved by incorporating a morning adjustment factor
2) Two BLM models consistently perform well (with morning adjustment)
   - Highest 3 of the previous 10 admissible days (*m3_3of10*)
   - Load-temperature regression model using data from the previous 10 admissible days (*m6_lt10day*)
3) Applying morning adjustment improves the performance of all models, both on bias and accuracy
4) Accounting for variability in building loads
   a) For buildings with high variability, averaging methods perform best in terms of error magnitude
   b) For buildings with low variability, most models perform well in terms of error magnitude
5) Importance of accounting for weather
   a) Only model *m6_lt10day (regression-based model)* consistently avoids significant bias for all buildings
6) Data quality also matters:
   - Removing outliers from weather data and adding basic schedule information to the selection of admissible days is likely to improve accuracy of all BLM
7) It may make more sense to define error tolerance criteria and choose a model that meets those criteria, than to pick a "best" model

Extras

Site	Avg	Min	Max	he10	he11	he12	he13	he14	he15	he16	he17	he18
ACWD	0.75	0.70	0.81	0.71	0.70	0.70	0.72	0.76	0.76	0.77	0.81	0.78
CCC_Arnold	0.83	0.77	0.88	0.78	0.77	0.77	0.83	0.87	0.85	0.88	0.87	0.81
CCC_Douglas	0.82	0.69	0.89	0.82	0.83	0.82	0.80	0.82	0.85	0.88	0.89	0.69
CCC_MDF	0.71	0.63	0.83	0.63	0.64	0.70	0.72	0.71	0.67	0.66	0.80	0.83
Centerville	-0.05	-0.14	0.03	-0.12	-0.04	0.00	0.01	0.01	0.03	-0.07	-0.09	-0.14
Chabot	0.49	0.10	0.59	0.47	0.50	0.56	0.58	0.54	0.56	0.55	0.49	0.10
Echelon	0.82	0.68	0.90	0.89	0.90	0.88	0.87	0.84	0.68	0.73	0.77	0.84
Gilead01	0.61	0.30	0.74	0.51	0.30	0.51	0.62	0.70	0.74	0.71	0.69	0.72
Gilead02	0.79	0.71	0.83	0.78	0.71	0.73	0.79	0.83	0.80	0.80	0.79	0.82
Gilead03	0.49	0.34	0.57	0.34	0.39	0.43	0.52	0.52	0.53	0.50	0.57	0.56
IKEA_Em	0.71	0.66	0.78	0.66	0.67	0.67	0.70	0.70	0.73	0.78	0.76	0.73
IKEA_EPA	0.77	0.72	0.82	0.75	0.82	0.72	0.79	0.76	0.75	0.77	0.78	0.79
IKEA_WSac	0.91	0.79	0.98	0.79	0.87	0.83	0.91	0.91	0.93	0.96	0.96	0.97
Irvington	-0.23	-0.35	-0.12	-0.24	-0.12	-0.12	-0.19	-0.17	-0.24	-0.33	-0.34	-0.35
ODC	0.75	0.65	0.87	0.87	0.79	0.74	0.68	0.65	0.66	0.71	0.81	0.87
OracleR	0.40	0.34	0.43	0.39	0.42	0.42	0.43	0.42	0.40	0.37	0.38	0.34
SafewayS	0.93	0.87	0.97	0.87	0.89	0.91	0.94	0.94	0.95	0.97	0.96	0.96
Solectron01	0.65	0.56	0.72	0.56	0.62	0.66	0.68	0.72	0.69	0.69	0.59	0.61
Solectron02	0.64	0.60	0.70	0.63	0.70	0.66	0.63	0.60	0.61	0.61	0.69	0.62
Solectron03	0.45	0.43	0.47	0.43	0.45	0.43	0.47	0.45	0.47	0.43	0.43	0.46
Solectron04	0.63	0.57	0.68	0.57	0.58	0.61	0.61	0.63	0.66	0.68	0.68	0.67
Solectron05	0.88	0.82	0.92	0.82	0.87	0.85	0.88	0.88	0.91	0.92	0.91	0.89
Solectron06	0.17	0.15	0.21	0.16	0.16	0.21	0.18	0.18	0.18	0.16	0.16	0.15
Solectron07	0.77	0.74	0.82	0.82	0.80	0.79	0.77	0.74	0.74	0.74	0.75	0.75
Solectron08	0.60	0.47	0.63	0.62	0.59	0.62	0.61	0.63	0.61	0.62	0.62	0.47
Solectron09	0.36	0.30	0.39	0.30	0.34	0.35	0.37	0.35	0.38	0.39	0.38	0.39
Svenhards	0.01	-0.06	0.10	0.07	0.10	0.07	0.03	-0.01	-0.06	-0.05	-0.06	-0.01
Sybase01	0.74	0.67	0.82	0.72	0.73	0.72	0.73	0.75	0.79	0.82	0.75	0.67
Sybase02	0.79	0.54	0.85	0.73	0.80	0.82	0.85	0.83	0.85	0.82	0.83	0.54
Target_Ant	0.83	0.73	0.88	0.80	0.73	0.78	0.80	0.85	0.87	0.88	0.87	0.87
Target_Bak	0.91	0.89	0.94	0.91	0.90	0.89	0.91	0.89	0.90	0.92	0.93	0.94
Target_Hay	0.83	0.71	0.90	0.71	0.79	0.82	0.82	0.85	0.85	0.85	0.85	0.90
WalmartF	0.97	0.96	0.97	0.96	0.96	0.96	0.97	0.97	0.97	0.97	0.97	0.97

Weather Sensitivity

The rank-order correlation coefficient (ROC) between building load and outdoor air temperature is shown, for each hour separately, for each building.

The ROC takes on values between plus and minus one.

Example event day: Office Building, Fremont, July 21st 2006